The generalized sustainability credit rating system

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Abstract This article describes the steps required to generalize a sustainability credit rating system based on the analytical hierarchy process. We argue that such systems are ideal for commercial banks to improve their lending processes. Starting with the model by Zeidan et al. (2015), we transform the SCSS from a closed to an open platform by adding country and industry variables, two additional possible answers, and an explicit way to generate forward default probabilities. Finally, we present a model for final reports that could be used for banks that use this or similar credit systems. The final reports are generated after initial tests on a database of 100+ public companies, with over 1,000+ Monte Carlo simulations conducted in six months following the initial assessments.

Keywords: Green banking; Credit rating systems; Analytical hierarchy process; Commercial banks; Sustainability credit score systems.
JEL Code: G24, Q01.

1. Introduction

According to Edmans (2022), ESG (Environmental, Social and Governance) is extremely important and nothing special because it's no better or worse than other intangible assets. That includes those that drive long-term value and create positive externalities for broader society, such as management quality, corporate culture, and innovative capability. Yet that does not mean markets efficiently incorporate this type of information. In fact, some funds seem to be building an "anti-ESG" movement, assuming that tackling climate change is a job for public officials (Mundy and Bryan, 2022). Here, we follow Edmans (2022) in the idea that ESG indicators are relevant and unremarkable and consider augmented credit rating systems that better incorporate intangible assets, of which many are ESG indicators.

Our goal is to provide an open platform general sustainability-related credit rating system. Previous attempts (e.g., Zeidan et al., 2015) have been closed platforms created for specific consumers, such as commercial banks. We provide the detailed methodology for an open platform sustainability

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credit-score system to facilitate financial institutions' abilities to overcome organizational inertia.

The inclusion of environmental and social elements in lending decisions has been advocated for and examined in the scientific literature for more than 20 years (e.g., Case, 1999; Cowton and Thompson, 2000; Acharya and Abuyuan, 2002). But there is currently no accepted technique for it. There are several causes for this (e.g., Rezaee and Tuo, 2019; Busco et al., 2020; Zeidan, 2022b), including the lack of agreement on which environmental issues should be taken into account by credit rating systems, the failure of any one method to outperform others, and the absence of established international regulatory requirements.

We argue that sustainability credit score systems that generate similar ratings to regular credit rating models are ideal for commercial banks to improve their lending processes. Imperatively, such systems must include upside and not only downside possibilities for the interaction between environmental and social drivers and financial performance. In addition, these systems must be able to generate ratings for companies of all sizes, not relying solely on publicly-available data. For that purpose, we provide a detailed methodology for a sustainability credit rating open platform based on analytical hierarchy processes. We generalize the closed-platform system in Zeidan et al. (2015) by, among other things, adding country and industry variables, two additional possible answers, and an explicit way to generate forward default probabilities. We also detail the final reports that could be used independently or alongside regular credit rating reports.

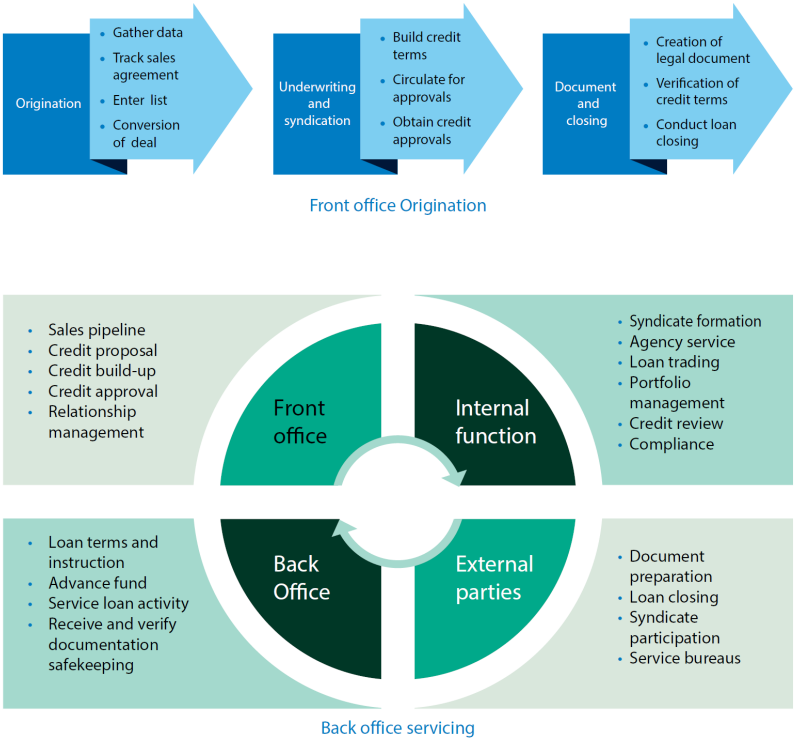
The following section discusses the reasoning for a stand-alone sustainability-related score rating system. The third section describes the methodological steps to generalize the SCSS. Finally, the last section concludes.

2. Why a general sustainability-related score rating system?

Our interest is in improving banks' lending decisions. In particular, the focus is on the process that involves evaluating prospective customers' likelihood of repaying loans in full (other stages include finding customers, assessing collaterals, designing loan agreements, and monitoring compliance). Figure 1 describes straight-through commercial banking lending processes.

Integrating climate and social risks in credit decision-making involves changing all steps of the lending process: origination, servicing, and asset management. In the present text, we are primarily concerned with credit risk assessment for lending origination. Specifically, by incorporating environmental and social factors into the gathering data step, banks could improve

Figure 1
Front office and back office straight-through lending processes



Sources: Kidder (2004) and Alexandar (2018).

their credit decisions, making them fairer (especially for external stakeholders), more robust, and consistent.

The literature has called for and analyzed the possibility of incorporating environmental and social factors into lending decisions for over twenty years (e.g., Case, 1999; Cowton and Thompson, 2000; Acharya and Abuyuan, 2002). However, we still don't have a standard method for it. There are a few reasons for it: there is no consensus on which environmental factors should be included in credit rating systems, no single method has outcompeted others, and no global regulatory mandates have emerged, among others.

A few robust initiatives come close to standardizing social and environmental factors in risk management models.

For instance, the Equator Principles[1] (EP) aim to serve as a common baseline for financial institutions to identify, assess and manage environmental and social risks when financing projects. However, the Equator Principles (now in its fourth version) deal with a narrow subset of commercial operations. It only applies to large infrastructure and industrial projects with capital costs of U$10 million and total aggregate loans of at least U$50 million.

ESG and reputation risk ratings encompass relative rankings of companies regarding environmental, social, and governance risks. Services like Sustainalytics[2] and Sustainable Fitch generate ESG ratings similar but more limited in scope to reports from credit rating agencies. Figure 2 displays a mock report from Sustainalytics, including the scale used in the report. As we can see, there are fewer categories than pure credit reports. But more importantly, such ratings are not aimed at impacting lending decisions. They aim to inform investors on how exposed are portfolios to material ESG issues.

Recent initiatives have tried to enhance the scope of sustainability risk management. For instance, Ascui and Cojoianu (2019) advance a natural capital (in the sense of ecosystem) credit risk assessment framework. Still, one crucial condition for banks to develop and implement robust sustainability credit rating systems is high-quality, actionable information as inputs. Thompson and Cowton (2004) show that bankers attach importance to firms' annual reports, notwithstanding their traditional limitations as a source of information on corporate environmental impact. They also note that some desire extensions to environmental disclosure, even if those desired developments are relatively narrow, mirroring banks' principal interest in protecting their loans.

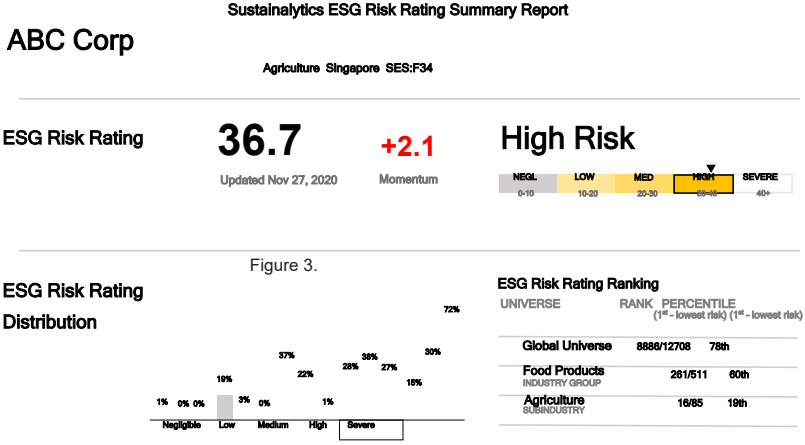
Since the mid-2000s, ESG indicators have emerged as the primary standard for disseminating financial and nonfinancial companies' social and environmental impact. However, there are two main barriers to ESG indicators as the central criteria for informing lending decisions: such indicators are mostly related to downside risk (Zeidan, 2022a), and there are currently over 360 ESG accounting standards globally (and ESG-related guidelines, such as regulations and standards, have grown from around 700 in 2009 to more than 1,700 today, according to The Economist.[3]) Some authors (e.g., Rezaee and Tuo, 2019; Busco et al., 2020) claim that societies face some form of ESG trap, the low information content of environmental reports that limits

[1] https://equator-principles.com/app/uploads/The-Equator-Principles_EP4_July2020.pdf.

[2] https://connect.sustainalytics.com/hubfs/SFS/Sustainalytics%20ESG%20Risk%20Rating%20-%20FAQs%20for%20Corporations.pdf.

[3] https://www.economist.com/business/2020/10/03/the-proliferation-of-sustainability-accounting-standards-comes-with-costs.

Figure 2
Mock report from Sustainalytics



Peers Table

Peers (Market cap $18.0 - $25.7bn)	Exposure	Management	ESG Risk Rating
1. Archer-Daniels-Midland Co.	58.7 High	46.3 Average	34.2 High
2. ABC Corp.	65.4 High	48.7 Average	36.7 High
3. New Hope Liuhe Co Ltd	59.2 High	23.9 Weak	46.4 Severe
4. Wen's Foodstuff Group Co., Ltd.	59.0 High	14.5 Weak	51.3 Severe
5. Tongwei Co., Ltd.	59.0 High	12.1 Weak	52.5 Severe

Negligible	Low	Medium	High	Severe
0 - 10	10 - 20	20 - 30	30 - 40	40+

the ability of investors and financial institutions to improve decision-making related to nonfinancial indicators.

Some initiatives aim to improve this landscape. The Corporate Sustainability Reporting Directive (CSRD) is the new European Union (EU) legislation requiring all large companies to publish regular reports on their environmental and social impact activities. Nearly 50,000 companies (15,000 in Germany alone) in the EU will be required to submit their report aligning with the CSRD on January 1, 2025, for the 2024 financial year. The CSRD is one of the measures within the Sustainable Finance Package adopted by the European Commission in April 2021 to help improve money flow toward sustainable activities across the EU.

However, although information content is undoubtedly a significant challenge, it is not the only barrier to robust sustainable lending processes. In the remaining section, we describe the primary methods for building credit rating systems and detail previous attempts at developing such methods.

2.1 Methods for sustainable lending

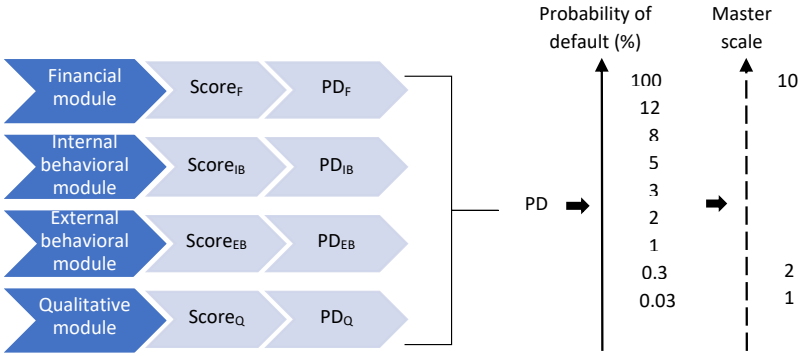
The steps for building a standard credit rating model are identification of the segment of interest (perimeter of applicability), definition of the event to be forecast (the default), analysis of the internal and external regulatory framework, analysis of processes, information technology procedures and data to support the credit unit and data availability, analysis of the portfolio, definition of the modality for dealing with outliers and exceptions, comparison and discussion with the business and credit experts (Izzi et al., 2012). Figure 3 describes the typical approach for building a credit rating model.

Credit ratings use quantitative and qualitative information based on different methods. These include multi-criteria decision-making (MCDM), as in the case of Zeidan et al. (2015), based on an analytical hierarchic process (AHP), Roy and Shaw (2021), designed from a fuzzy TOPSIS, and Nabeeh et al. (2021), developed through a Neutrosophic Multiple-Criteria Decision-Making Framework (N-MCDMF).

Bonsall et al. (2017) show that differences in the credit rating agencies' methodologies result in differences in rating properties. In particular, they focus on differences in information processing constraints between a rating agency that utilizes qualitative analysis and direct access to borrowers' management in its rating process compared to one that does not. They also find that as information uncertainty about borrowers increases, the ratings accuracy, informativeness, and timeliness of the agency without direct access decrease relative to the agency with that access.

This direct access to detailed information about borrowers motivates the

Figure 3
Main steps in the development of statistical models



Source: Izzi et al. (2012).

Sustainability Credit Score System (SCSS, Zeidan et al., 2015). It is based on the analytic hierarchy process methodology. Its goal is to inform lending decisions by integrating sustainability into regular credit reports. With a bank as its end user, the SCSS would work by inducing changes in lending decisions regarding credit availability and interest rates. For instance, banks that complement their regular credit score with a sustainability one would have better information to decide on the price and quantity of lines of credit. Also important is that the central condition for the generalization of the SCSS is the use of private information. We argue that this is one of the characteristics that makes the system stand out as an improvement over ESG ratings.

2.2 Private versus public information, private versus public companies

There is a common misconception that credit ratings rely almost exclusively on quantitative information, with their outputs robustly derived from unambiguous statistical models. But as Ganguin and Bilardello (2005) have noted: "a diligent credit evaluation of a company's financial performance and profile cannot and should not be done without an understanding of the level of qualitative risk inherent in the entity." ESG ratings are mainly designed for use by investors, so, naturally, they are based on public information. It is also why several sustainability-related ratings are only available for public companies; they are mostly (but not exclusively) built from self-reported ESG indicators.

The SCSS has been designed to encompass ratings for all types of companies, public and private, large and small. Its methodology is initially designed for account managers of commercial banks to input the required information to generate the final scores. Thus, it uses account managers' private information on their clients. Account managers are responsible for filling out the questionnaires, which tap on their private information, that generate standard scores. In that sense, it is similar to how regular credit ratings are implemented.

Generalizing the SCSS requires resolving the tension between public and private information. Limiting it to the former would likely make it easier to redesign it but would limit its adoption by commercial banks and other financial institutions. After all, only a fraction of banks' clients are listed companies. Institutions must create credit reports for all their lending operations. For small and medium-sized companies, banks mainly acquire credit bureaus' reports when available and complement them with proprietary information or build their own reports.

There are significant limits to the public information about companies' environmental and social impacts. Robust credit reports require consistent data for backtesting, but firms' ESG disclosure practices are not uniform (Zeidan, 2022a). For instance, firm-level variables explain most variation in ESG disclosure (Yu and Luu, 2021), disclosure scores are sensitive to outliers (Baldini et al., 2018), and profitable and mature firms disseminate more climate-related information (Drempetic et al., 2020).

Standardized private information allows for the evolution of robust credit ratings. Part of the appeal of the SCSS is that it is supposed to be used by commercial banks that can train their account managers and improve the ratings from each round of ratings generated by them. Thus, the main challenge with generalizing the SCSS for different end users is dealing with disparate expectations, abilities, and access to private information. In Section 3, we describe how we resolve these issues, although only higher adoption would allow researchers to check for the robustness of the final rating system.

2.3 How do banks incorporate information into "green" lending today?

There is no significant need to motivate green credit rating systems as many firms face climate risks. However, there is still knowledge to be gained by relating the recent scientific literature to the SCSS. There is evidence that climate and credit risk are highly correlated (Capasso et al., 2020), which could drive banks to accelerate the incorporation of climate factors in regular credit risk models. In fact, it is somewhat of a puzzle why that has not already happened, with some authors (e.g., Zeidan, 2022b) arguing that orga-

nizational inertia is a more substantial barrier than previously thought. More importantly, Capasso et al. (2020) find that the positive relationship between corporate default risk and carbon footprint is stronger following the Paris Agreement, which may support the argument that banks must adapt or die.

Some of that risk is already priced in the bonds issued by the largest companies. Apergis et al. (2022) find that firms within the S&P 500 with solid ESG scores benefit from lower bond spreads and better bond ratings than firms with weaker ESG scores. Of course, most companies worldwide do not issue bonds, even though the market for green bonds is maturing (e.g., Ehlers and Packer, 2016, 2017; Hachenberg and Schiereck, 2018; Chang et al., 2020) and expanding (Barua and Chiesa, 2019).

There is one counterargument to the need for commercial banks to incorporate nonfinancial performance into standard credit rating systems: banks already charge higher interest rates to firms with higher environmental risks.

Weber et al. (2010, 2015) indicate that sustainability criteria can be used to predict the financial performance of a debtor and improve the predictive validity of the credit rating process. Weber (2012) notes that Canadian banks systematically examine environmental risks for credits, loans, and mortgages but without clear benchmarks (at the time).

In addition, Fard et al. (2020) show, using a sample of 27 countries between 1990 and 2014, that banks charge higher interest rates and adjust other contractual features of their loans when lending to firms facing more stringent environmental regulations. They also show that firms facing such regulations have fewer participants in their loan syndicates, higher bankruptcy risk, and lower credit ratings, despite reducing their leverage. Thus, they conclude that banks' lending practices are already environmentally sensitive. In addition, Guiral et al. (2021) suggest that lenders use CSR performance as a proxy for borrowers' integrity. However, although Semet et al. (2021) confirm that extra-financial criteria are integrated into bond pricing, they find that credit rating agencies undermine the impact of climate change and environmental topics on a country's creditworthiness.

Another relevant empirical evidence for the present context comes from Wellalage and Kumar (2021). On a sample of 3,915 unlisted firms, they find that companies with better environmental performance received approximately 6.4% higher loans (as a ratio of total sales) but that environmental performance does not affect loan duration and collateral requirement, indicating no spillover economic effect of corporate environmental performance on loan conditions.

Although there is evidence that ESG indicators are already incorporated into credit risk models, banks don't necessarily do that systematically. For

instance, Zhou et al. (2022) show that information and expertise asymmetries limit commercial banks' abilities to evaluate the credit risk of green lending. Moreover, almost all the discussions on "green" lending and bonds focus on downside risks from incorporating ESG "risks" (for a discussion on why ESG indicators are not risk factors, see Zeidan, 2022a) into regular credit risk models.

In the end, we have indirect evidence that commercial banks already use nonfinancial information for lending decisions, which isn't surprising. Still, the strongest evidence is that banks use that information indirectly. Take Fard et al. (2020), for instance. They find that financial institutions use environmental regulation as a proxy for climate-related risks. Banks control for some of the ESG indicators in corporate lending. We argue that generalizing credit score systems to incorporate socio-environmental information comprehensively for banks can make financial markets more relevant in mitigating climate change. In addition, rating systems should incorporate upside possibilities and not solely downside risks. Banks don't have robust incentives to use ESG indicators in lending decisions because that would only make credit scarcer and more expensive. Ideally, banks would reduce interest rates for more sustainable and innovative companies through better credit ratings and not only look at increased default probabilities. Thus, we discuss how to generalize sustainability credit systems based on the SCSS (Zeidan et al., 2015), which uses internal information and upside possibilities to generate companies' nonfinancial ratings.

3. Generalizing sustainability credit risk systems

Our goal is to describe an implementable generalized sustainability credit score system launched as a financial service open to subscribers in early 2022, the Sona Sustainability Credit Score System. It is based initially on the SCSS (Zeidan et al., 2015), but it has one crucial enhancement: we have expanded the system for any end-user interested in generating a sustainability credit report. That includes commercial banks, insurers, investors, and any type of financial institution.

The SCSS model is unique because it provides a single sustainability risk assessment framework through which companies and entities of different sizes, geographies, sectors, and industries can all be reliably measured, scored, and ranked. This system enables an analyst to compare, for example, the sustainability performance of a wind farming company in Ghana and a mining company in Norway, all on the same measurement scale.

The central tradeoffs in generalizing a credit score system refer to the nature of information and the compatibility between scores generated by dif-

ferent analysts. When used by a commercial bank, it is straightforward to train analysts or account managers who will input the data to guarantee compatibility and refine the final product. In addition, the SCSS has been tested in a single sector, the sugar industry in Brazil. Expanding the system for any industry in all countries and the information asymmetry across end users provides formidable challenges.

The SCSS is a straightforward application of an analytical hierarchical process. It is composed of six matrices for the six sustainability dimensions, each matrix $A_i = (a_{ij})_{1 \leqslant i,j \leqslant n}$, in which

$$a_{ij} = \begin{cases} 1, & \text{if } i = j, \\ 1/a_{ji}, & \text{if } i \neq j, \end{cases} \tag{1}$$

and a weighting matrix for the six dimensions. For each dimension, A_i is composed of 5 questions, and a final questionnaire of 30 questions is developed from the analytical model, yielding a final sustainability credit score that ranges from 0 to 1 (Zeidan et al., 2015). For each question, analysts must choose one of three options, representing the three main paths for sustainable development: business as usual (BAU), sustainable business (SB), and future sustainable business (FSB). As Zeidan et al. (2015) describe, BAU refers to the present stage in which the industry practices are directly related to past practices, which may or may not be sustainable; SB is a future stage (five-year horizon), resulting from the adoption of new sustainable practices by firms. These are mainly derived from emerging technologies, new commercial practices, and evolving legislation; FSB is a future stage (20-year horizon) marked by the foreseen role of the industry in a sustainable path that would allow continuing economic, social, and environmental development.

There are several challenges to generalizing the SCSS from closed to open platforms, from single to multi-industries, and from one to any country. The crucial ones are the number and content of the sustainability paths must be redefined, questions and weights must be redesigned, and a new set of country-specific weights must be created. In the following subsection, we provide a guide for creating an open platform where any end user can generate an organization's sustainability credit score.

3.1 The initial guide to inputting information for the SCSS

The model is based on relative comparisons. Thus comparisons between indicators must be consistent for the results to be meaningful. The analyst must choose, for each indicator, one of four options: NBAU (which indicates that a company is worse than the industry's average), BAU, SB, or FSB. The

simplest way to interpret these options is to rank companies as: below average, average, above average, and one of the best. For each of the 18 indicators, which expands on the initial set in Zeidan et al. (2015), an analyst must choose one of the four alternatives for the company under examination.

But before answering the specific questions regarding the company for which the sustainability credit rating is being generated, the analyst must answer a few questions that will establish the comparison group for the company under examination.

The antecedent process is due to the credit rating, as is standard, making relative comparisons. Thus, there must be clear benchmarks for each company to be ranked. There are two categories to build the comparison groups (usually for companies in the same industry).

The first category determines if the evaluated company faces the steepest, major, or minor sustainability challenges. For that purpose, three primary variables must be considered: where the company is located, the industry that is the primary source of profits for the company (for instance, by considering the NAICS or SIC identification codes), and the relevant products or services that are the primary sources of environmental and social issues.

It should be noted that the system is qualitative, as is the case with many facets of credit rating systems. In that sense, there are no unique, unambiguous criteria for some classifications below. Still, the system is robust as long as analysts are consistent (as the number of responses increases, consensus calls can be developed to improve the system).

Thus, to make the process of filling out the questionnaire simple and efficient, the analyst must consider the binary choices below:

Region 0 if the company operates in a region with low-quality institutions; 1 otherwise.
Industry 0 if the industry is rife with environmental or social challenges (mining, oil & gas, land-intensive agricultural production, etc.); 1 otherwise.
Products 0 if the production and sales of the firm's primary goods and services bring significant negative externalities; 1 otherwise.

Usually, there will be a strong correlation between industry and products, but not always. For instance, a company that repairs oil platforms may be classified as part of an industry rife with environmental challenges. Still, their services may not pose significant challenges to the ecosystem.

The initial classification will result in the following comparison groups, ordered through the sum of the binary variables ($S = \text{Region} + \text{Industry} + \text{Product}$; $0 \leqslant S \leqslant 3$):

1. The most significant sustainability challenges ($S = 0$)

2. Major sustainability challenges ($S = 1$)
3. Minor sustainability challenges ($S \geqslant 1$)

The second goal is related to the information at the analyst's disposal. There are three possible alternatives: no company-specific information ($D = 0$); low-quality information ($D = 1$); and high-quality information ($D = 2$). In many cases, there will not be detailed and trustworthy information about some indicators ($D = 0$), but there will be information about others ($D \geqslant 0$). The standard classification when there is no actionable information for a certain indicator is BAU. When there is information available, there are two options:

(a) Low-quality information ($D = 1$): this category incorporates company-generated data that cannot be audited, secondary information, such as reports from industry associations that is not detailed, or other types of information that are better than having no information but cannot be trusted wholesale.
(b) High-quality information ($D = 2$): data tied explicitly to the indicator under consideration from reputable sources that can be trusted at face value. Data generated by the company can be classified as high-quality if the information is transparent; data cannot be easily manipulated and/or reputable third parties have supervised or audited the data generation process or final reports.

The comparison groups above lead to the following rules for filling out the questionnaire. For a specific indicator:

FSB Analysts should classify companies in this category only if high-quality information is available.
Even so, when $S = 0$, this category is unavailable unless there are exceptional circumstances.
When $S = 1$, companies must be in the top 5% among their comparison group to be classified as FSB. Companies should be the main driving force behind decarbonizing their industries for that particular indicator, or they should present an innovative way to deal with the issue at hand.
When $S \geqslant 1$, companies must show actual pursuits to lower their negative environment or social impact to be classified as FSB. Information should describe the actions taken by the companies and how it tracks the effects of their measures.
SB When $S = 0$, this category is only available if high-quality information indicates that the company is committed to reducing its harmful environmental or social impact. Information should describe the actions taken by the com-

panies and how it tracks the impact of their measures. There should be clear evidence that the company does not incur in greenwashing.
When $S = 1$, this category is only available if the information indicates that the company is committed to reducing its deleterious environmental or social impact. Information should describe the actions taken by the companies and how it tracks the effects of their measures.
When $S \geqslant 1$, the analyst should classify the company as S.B. if it exceeds that indicator's industry standards.

BAU BAU is the standard answer if the analyst has no reason to consider that the company is different from its peers for that indicator.
If high-quality information is available, a company should be classified as BAU if there are no significant risks to its operations or society about the specific indicator under consideration.
If there is low-quality information, the analyst must consider material risks to society from the company's operations regarding that indicator.

NBAU The analyst should select NBAU with evidence of higher risks than comparable companies for the indicator under consideration, e.g., evidence of repeated fines about the issue, the use of old production methods, the hidden effects of their operations, and active opposition to improved regulatory standards.

Below are some developed questions so analysts can rank companies regarding their nonfinancial performance. Unfortunately, there is no initial way to generate questions that yield unambiguous responses. However, that is not a significant hurdle. As with every credit score system, questions are supposed to be refined as results accumulate. For instance, if there is an indication that the dispersion of the answers from analysts for certain companies is exceptionally high, the questions can be rewritten to limit ambiguity.

The examples below describe the first version of the questions related to the eco-efficiency dimension (Figure 4).

3.2 Adding options and further changes after initial tests

The five key areas of further development required to generalize the SCSS covered in this paper are the inclusions of country impact, industry and sector impact, additional rating answer options, sustainability forward default probability, and credit rating score comparisons. Within each area are certain limitations and testing requirements in the application to company ratings to normalize relative to the rating of industry peers.

Figure 4
Initial version of eco-efficiency questions for the generalized SCSS

1. Eco-Efficiency			
NBAU	BAU	SB	FSB
Water management			
Does not meet the legal requirements	Compliance with law	Has concrete actions to make consumption and water capacity compatible	Leader in its industry regarding water management
Waste management			
Does not meet the legal requirements/ poses a grave risk to adjacent ecosystems.	Compliance with law/ Accepts the possibility of disasters	Creates little waste and/or promising practices impede potential disasters.	Leader in its industry regarding waste management. E.g., reuses most waste generated; uses it as biofuel in small electricity generation plants, etc.
Land use, including deforestation			
Company is set on contested areas, regular conflicts with locals; uncertain if operations are linked to deforestation	Compliance with the law and/or following standard practices.	Investments in land revitalization, including reforesting in company land, if applicable. Must go beyond regulatory standards. Publishes comprehensive public reports.	Has concrete actions to foster biodiversity; publishes and tracks biodiversity action plans (focus on actions); prioritizes, monitors and schedules actions related to land-use improvements.
Disaster Resilience			
The company's operations are particularly prone to natural disasters like floods and hurricanes.	Compliance with the law and/or following standard practices.	Risk management practices include concrete plans for natural disasters and built-in redundancies. Service provision may not suffer from disaster risks. The company is well-insured financially.	Has concrete actions to mitigate natural disaster risks, working alongside the community and regulators to maintain its "social capital" even if natural disasters occur.
Certifications			
Company does not have standard certifications and thus cannot access specific markets. Company is regularly fined for lack of environmental certifications.	Compliance with the law and/or following standard practices.	Company has advantages over its competitors for holding certifications that are not standard. Company works with NGOs and other stakeholders to improve its operations and the supply chain	Company is proactive in disseminating best practices. Holds almost all certifications and is the industry leader in the subject.

3.2.1 Country impact

When starting a new company rating, the user is asked to select the country in which the company being rated is based or headquartered. There are 193 countries on the list of country options. According to the U.N. Country Sustainability Report, each of these countries is ranked by their overall score. The overall score measures the progress toward achieving all 17 Sustainable Development Goals (SDGs) as a percentage of SDG achievement, where a score of 100 indicates that all SDGs have been achieved. At the top of this list in descending order are Finland, Denmark, Sweden, and Norway, with scores ranging from 86.51(%) to 82.35(%) as of 2022.

The country selected impacts the company's final score being rated based on the difference between the relevant country's sustainability development score from the average (mean) score of all 193 countries, which is then divided by two. For example, if the country of the company being rated is Japan which has a country score of 79.85(%), this is subtracted from the average (mean) score of 62.09(%) and divided by 2, giving a final country impact score of +8.88(%). Suppose the company's country score is lower than the average (mean) country score. In that case, this will reduce the final sustainability rating of the company in question. For example, suppose the country of the company being rated is Liberia, with a 48.65(%) score. In that case, this is subtracted from the average (mean) score of 62.09(%) and divided by 2, giving a final country impact score of −6.72(%).

The current approach is pragmatic. The final country impact score is added to (or subtracted from) the result of the Sustainability Credit Score System, producing a final score and rating. Therefore, two companies that are identical in all other sustainability metrics aside from the countries in which they are based have different sustainability credit scores. It seems unfair to discriminate against companies geographically, but this is today's market reality. The current approach approximates the difference between sovereign ratings, incorporating these into individual credit ratings, as is standard practice.

3.2.2 Industry and sector impact

Similarly to the country's impact score, the industry and sector also affect the final sustainability credit score.

Economic activities can broadly be classified in several ways. One of the more widely used classification methods puts industries into one of three sectors: primary (extraction and agriculture), secondary (manufacturing), and tertiary (services). Some add quaternary (knowledge) or quinary (culture and

research) sectors. Different industry classification methods include the International Standard Industrial Classification of All Economic Activities (ISIC), the North American Industry Classification System (NAICS), the Standard Industrial Classification (SIC), and the Bloomberg Industry Classification Standard (BICS). Users are asked to select the relevant industry from a list of 60 options.

All industry option belongs to one of the three sectors. The weightings differ for each sector based on the companies' exposure to the indicators within the six dimensions. For example, industries in the manufacturing sector have the highest exposure to environmental dimension impacts (environmental protection and eco-efficiency). In contrast, service companies have higher exposure to social dimension impacts (socio-economic and social progress).

3.2.3 Additional rating answer options

The four rating options initially available as part of the SCSS are NBAU, BAU, SB, and FSB. Two additional rating options are introduced: Sustainability Default (SD), indicating an adverse sustainability event in the past 12 months, and a Not Applicable (N/A) option, where the specific indicator in question is not relevant to the entity being rated.

The inclusion of the Sustainability Default rating options in the analytical methodology increases the lower end of the range of possible results (of the sustainability credit score) from 1/100 (1%) up to 100/100 (100%). An SD rating represents a score of 1%, NBAU is 25%, a BAU of 50%, S.B. 75%, and FSB 100%. This scale allows for a standardized measurement framework that can be reliably and intuitively tested across companies and sectors.

Moreover, the N/A option accounts for not all of the indicators across the six dimensions applies. Thus, non-relevant indicators have no impact on the final score. Finally, for consistency, the weight matrices for the AHP are standardized, as shown below (Figure 5), following Zeidan et al. (2015).

3.2.4 Forward default probability

Another feature of the generalized SCSS is the creation of credit reports that include a Sustainability Forward Default Probability, the probability of a sustainability default occurring over five years for the rated company.

A sustainability default explicitly indicates the company's exposure to adverse ESG or sustainability events. Infamous such events include the Deepwater Horizon oil spill in 2010 and Volkswagen falsifying emission tests due to poor governance resulting in a loss of $33.3 billion in fines, penalties, financial settlements, and buyback costs. It can be extended to incorporate climate

Figure 5
Weight matrices for the six dimensions and initial four options for analysts

	EE	SE	ES	EP	EG	SP
EE	1	1	1	3	3	3
SE	1	1	1	3	3	3
ES	1	1	1	3	3	3
EP	1/3	1/3	1/3	1	1	1
EG	1/3	1/3	1/3	1	1	1
SP	1/3	1/3	1/3	1	1	1

	FSB	SB	BAU	nBAU
FSB	1	1/3	1/5	1/9
SB	3	1	1/3	1/5
BAU	5	3	1	1/3
nBAU	9	5	3	1

risks, such as the severe flooding in Thailand in 2011, which disrupted automotive and technology supply chain networks, causing an estimated $46.5 billion in economic damages.

The methodology used to assess a company's sustainability forward default probability works by looking at the sustainability ratings of a database of public companies for each year over the past ten years and calculating their average percentage of sustainability default events over the period.

This methodology's primary limitation is the assumption that past averages are informative. As the landscape of ESG and sustainability is evolving rapidly, we will likely see less correlation between market responses to past climate and social events. To overcome this limitation, the plan is to conduct regression analyses on the historical sustainability performance of the universe of companies quarterly.

3.2.5 Credit rating score comparisons

For a particular company, the sustainability score is the weighted average of the 30 indicators (questions) under the six dimensions (economic growth, environmental protection, social progress, socio-economic development, eco-efficiency, and socio-environmental). This score is then adjusted for a country's impact and normalized relative to industry peers.

The final sustainability score for the entity (e.g., 77%) is matched to a corresponding final sustainability rating (e.g., A+), a credit grade equivalent (e.g., upper medium grade), and a classification of whether or not this equates to an investment grade rating or not. The final sustainability score of the as-

sessed entity corresponds to a rating between AAA (extremely strong) and D (sustainability default). All ratings between AAA and BBB−are considered 'investment grade,' and those between BB+ and D are considered non-investment grade. These assessments of company performance are not absolute but explicitly intended to be relative to the standards and performance of a company's industry peers.

The choice for this particular scoring system is straightforward: its similarity to the standard credit rating systems used by global rating agencies.

3.2.6 Initial adjustments

The primary objective of the generalized SCSS is to assess companies' sustainability and ESG exposure and opportunities, generate consistent, reliable results and provide valuable insights on the sustainability creditworthiness of a given counterparty.

Even though the goal is for a system that can be used to generate ratings for companies of all sizes, the framework of the generalized SCSS model was initially tested on a database of 100+ public companies, with over 1,000+ Monte Carlo simulations conducted in six months following the initial assessments. Although the general framework of the initial model has remained unchanged, there have been several refinements to the weightings applied to both the country and sector/industry inputs to align further the assessments and results of company performance relative to industry peers.

Macro data at the segment and geographic levels are continuously collected from academic and NGO datasets (e.g., World Bank, Transparency International, and US EPA), company disclosures (sustainability reports, proxy reports, AGM results, etc.), government databases, and other stakeholder sources regarding specific companies. For the model, essential data include weekly monitoring of controversies or sustainability default events by companies or other government entities.

The Sustainability Credit Risk Committee reviews all new industry developments and model changes. In subsequent steps, a formal in-depth quality review takes place, including quality checks of data and rating results, industry and market-lead oversight, and sustainability accounting standards and reports. Furthermore, the plan is for an in-depth review of the entire model framework to be conducted annually. This review will examine the critical issues assigned to the various dimension and indicators and the weights applied to each sector and industry model. This process may also identify emerging issues and those that have become less significant.

The framework helps to attenuate information biases by extracting private information possessed by the analysts that use the credit score system. Many

outsiders, such as account managers and analysts, have firm-specific information, but there is no structured way to extract it into a coherent framework. Remaining expertise biases could be limited by using robustness checks on the reports generated by the end users of the generalized SCSS. For instance, if dozens of analysts create reports for the same company, we can improve the model by checking for omissions in the questionnaires or patterns from the inputted answers. Finally, the system could also be used by firms, with workers independently filling out the questionnaires so managers could come out with reports for internal use.

Appendix 1 brings an example of a results report for the generalized SCSS. There, we detail all the information for the report's replication for developers that would like to create similar systems based on the present methodology.

4. Final comments

Ideally, commercial banks would generate sustainability-related ratings or modify their existing credit rating systems to incorporate nonfinancial performance explicitly. The present article details all the steps required to generalize a sustainability credit rating system (based on Zeidan et al., 2015) from a closed to an open platform.

The first step to generalize the SCSS includes adding three primary variables: where the company is located, the industry that is the primary source of profits for the company (for instance, by considering the NAICS or SIC identification codes), and the relevant products or services that are the primary sources of environmental and social issues. The second step is the inclusion of two rating answer options. Then, we determine the weightings for arriving at a sustainability forward default probability, and, finally, we make credit rating score comparisons.

The main output is the Sustainability Forward Default Probability for the rated company. That reflects the possibility of a sustainability default occurring over five years. It should be noted that the system is qualitative, as is the case with many facets of credit rating systems. In that sense, there are no unique, unambiguous criteria for some classifications below. Still, the system is robust as long as analysts are consistent (as the number of responses increases, consensus calls can be developed to improve the system).

The current model may provide a way for society to overcome the ESG trap, the low information content of environmental reports that limits the ability of investors and financial institutions to improve decision-making related to nonfinancial indicators (e.g., Rezaee and Tuo, 2019; Busco et al., 2020; Zeidan, 2022a). Although there is evidence that ESG indicators are already

incorporated into credit risk models, banks don't necessarily do that systematically (Zhou et al., 2022). We argue that the present model can help commercial banks overcome information and expertise asymmetries in evaluating the credit risk of green lending by extracting private information from account managers, analysts, insiders, and other market agents.

References

Acharya, A. and Abuyuan, A. M. T. (2002). A decade of environmental lending: A review of the World Bank's environment portfolio during the 1990s, *Environment strategy papers no. 6*, World Bank.

Alexandar, A. M. (2018). Straight-through processing in commercial lending: commercial banking lending perspective, *White paper*, Infosys.

Apergis, N., Poufinas, T. and Antonopoulos, A. (2022). ESG scores and cost of debt, *Energy Economics* **112**: 106186.

Ascui, F. and Cojoianu, T. F. (2019). Implementing natural capital credit risk assessment in agricultural lending, *Business Strategy and the Environment* **28**(6): 1234–1249.

Baldini, M., Maso, L. D., Liberatore, G., Mazzi, F. and Terzani, S. (2018). Role of Country- and Firm-Level Determinants in Environmental, Social, and Governance Disclosure, *Journal of Business Ethics* **150**(1): 79–98.

Barua, S. and Chiesa, M. (2019). Sustainable financing practices through green bonds: What affects the funding size?, *Business Strategy and the Environment* **28**(6): 1131–1147.

Bonsall, S. B., Leone, A. J., Miller, B. P. and Rennekamp, K. (2017). A plain English measure of financial reporting readability, *Journal of Accounting and Economics* **63**(2): 329–357.

Busco, C., Consolandi, C., Eccles, R. G. and Sofra, E. (2020). A Preliminary Analysis of SASB Reporting: Disclosure Topics, Financial Relevance, and the Financial Intensity of ESG Materiality, *Journal of Applied Corporate Finance* **32**(2): 117–125.

Capasso, G., Gianfrate, G. and Spinelli, M. (2020). Climate change and credit risk, *Journal of Cleaner Production* **266**: 121634.

Case, P. (1999). *Environmental risk management and corporate lending: A global perspective*, Woodhead Publishing.

Chang, K., Feng, Y. L., Liu, W., Lu, N. and Li, S. Z. (2020). The impacts of liquidity measures and credit rating on corporate bond yield spreads: evidence from China's green bond market, *Applied Economics Letters* **28**(17): 1446–1457.

Cowton, C. J. and Thompson, P. (2000). Do Codes Make a Difference? The Case of Bank Lending and the Environment, *Journal of Business Ethics* **24**(2): 165–178.

Drempetic, S., Klein, C. and Zwergel, B. (2020). The Influence of Firm Size on the ESG Score: Corporate Sustainability Ratings Under Review, *Journal of Business Ethics* **167**(2): 333–360.

Edmans, A. (2022). The end of ESG, *Financial Management* **n/a**(n/a): 1–15.

Ehlers, T. and Packer, F. (2016). Green Bonds – Certification, shades of green and environmental risks, *Technical report*, Bank for International Settlements.

Ehlers, T. and Packer, F. (2017). Green bond finance and certification, *BIS Quarterly Review* .

Fard, A., Javadi, S. and Kim, I. (2020). Environmental regulation and the cost of bank loans: International evidence, *Journal of Financial Stability* **51**: 100797.

Ganguin, B. and Bilardello, J. (2005). *Standard & Poor's Fundamentals of Corporate Credit Analysis*, McGraw-Hill, New York, NY.

Guiral, A., Moon, D., Perez-Garcia, J. and Byun, J. (2021). Do affective reactions to sustainability performance unintendedly influence lending decisions?, *Corporate Social Responsibility and Environmental Management* **28**(6): 1635–1646.

Hachenberg, B. and Schiereck, D. (2018). Are green bonds priced differently from conventional bonds?, *Journal of Asset Management* **19**(6): 371–383.

Izzi, L., Oricchio, G. and Vitale, L. (2012). *Basel III Credit Rating Systems*, Palgrave Macmillan UK.

Kidder, L. A. (2004). Straight-Through Processing in Commercial Lending: A Solution Waiting for Awareness of the Problem, *Commercial Lending Review* **19**: 9.

Mundy, S. and Bryan, K. (2022). Can Vivek Ramaswamy take down ESG?, *Newspaper article*, Financial Times.

Nabeeh, N. A., Abdel-Basset, M. and Soliman, G. (2021). A model for evaluating green credit rating and its impact on sustainability performance, *Journal of Cleaner Production* **280**: 124299.

Rezaee, Z. and Tuo, L. (2019). Are the Quantity and Quality of Sustainability Disclosures Associated with the Innate and Discretionary Earnings Quality?, *Journal of Business Ethics* **155**(3): 763–786.

Roy, P. K. and Shaw, K. (2021). Modelling a sustainable credit score system (SCSS) using BWM and fuzzy TOPSIS, *International Journal of Sustainable Development & World Ecology* **29**(3): 195–208.

Semet, R., Roncalli, T. and Stagnol, L. (2021). ESG and Sovereign Risk: What is Priced in by the Bond Market and Credit Rating Agencies?, *SSRN Electronic Journal* .

Thompson, P. and Cowton, C. J. (2004). Bringing the environment into bank lending: implications for environmental reporting, *The British Accounting Review* **36**(2): 197–218.

Weber, O. (2012). Environmental Credit Risk Management in Banks and Financial Service Institutions, *Business Strategy and the Environment* **21**(4): 248–263.

Weber, O., Hoque, A. and Islam, M. A. (2015). Incorporating environmental criteria into credit risk management in Bangladeshi banks, *Journal of Sustainable Finance & Investment* **5**(1-2): 1–15.

Weber, O., Scholz, R. W. and Michalik, G. (2010). Incorporating sustainability criteria into credit risk management, *Business Strategy and the Environment* **19**(1): 39–50.

Wellalage, N. H. and Kumar, V. (2021). Environmental performance and bank lending: Evidence from unlisted firms, *Business Strategy and the Environment* **30**(7): 3309–3329.

Yu, E. P.-y. and Luu, B. V. (2021). International variations in ESG disclosure – Do cross-listed companies care more?, *International Review of Financial Analysis* **75**: 101731.

Zeidan, R. (2022a). Why don't asset managers accelerate ESG investing? A sentiment analysis based on 13,000 messages from finance professionals, *Business Strategy and the Environment* **31**(7): 3028–3039.

Zeidan, R. (2022b). Obstacles to sustainable finance and the covid19 crisis, *Journal of Sustainable Finance & Investment* **12**(2): 525–528.

Zeidan, R., Boechat, C. and Fleury, A. (2015). Developing a Sustainability Credit Score System, *Journal of Business Ethics* **127**(2): 283–296.

Zhou, X. Y., Caldecott, B., Hoepner, A. G. F. and Wang, Y. (2022). Bank green lending and credit risk: an empirical analysis of China's Green Credit Policy, *Business Strategy and the Environment* **31**(4): 1623–1640.

A. The output of the generalized SCSS

This appendix reports calculation results for SONA Sustainability Credit Score System.

Summary – Model Information

Company Name	CSB
Country	Denmark
Model	SCSS1
Sector	Services
Industry	Education
Analyst	Rodrigo Zeidan

Rating Date	11-07-2022
Comparison Group Scores	
Country	1 or 0
Sector	1 or 0
Industry	1 or 0

Generalized SCSS Results – Summary

Final Sustainability Score	78%
Final Sustainability Rating	A+
Credit Grade Equivalent	Upper Medium grade
Investment Grade? (BBB−or above)	Yes

Generalized SCSS Results - Current

Environmental Protection	
Indicator	Rating
Business model	SB
Greening of supply-chains	SB
CO2 and other climate-related emissions	BAU
Environmental auditing and certifications	BAU
Energy consumption	SB

Eco-Efficiency	
Indicator	Rating
Water management	SB
Waste management	SB
Land use	N/A
Disaster resilience	N/A
Certifications	SB

Economic Growth	
Indicator	Rating
Corporate governance	SB
Innovation and long-term viability	BAU
Quality of economic growth opportunities	NBAU
Equipment and machinery	SB
Types of consumers	SB

Socio-Environmental	
Indicator	Rating
Reporting on labor and environmental issues	BAU
Labour and environmental model	SB
Corruption	FSB
Funding	BAU
Industry associations	FSB

Social Progress	
Indicator	Rating
Social License to Operate	BAU
Regulatory changes	BAU
Sourcing	SB
Diversity	BAU
Relationship with stakeholders	SB

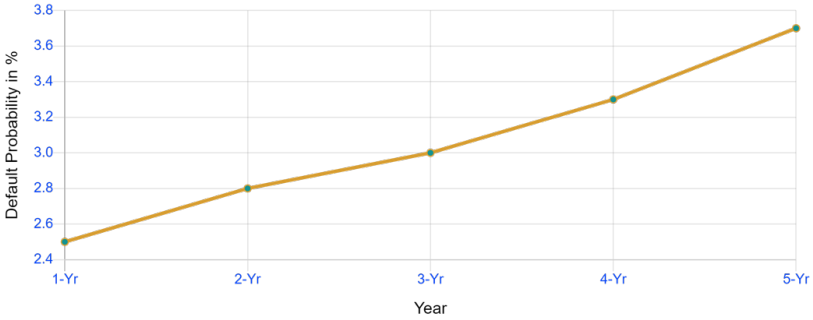
Socio-Economic	
Indicator	Rating
Labor costs	BAU
Labor training and conditions	SB
Worker “s health and risk of accidents	SB
Outsourcing and supply chain risks	N/A
Data disclosure	SB

Generalized SCSS Results – Forecast

	1-Year	5-Year
Sustainability Default Probability	2.5%	3.7%
Sustainability Rating	A+	A+
Percentile	25%	25%

	Forward Sustainability Default Probability
1-Year	2.5%
2-Year	2.8%
3-Year	3.0%
4-Year	3.3%
5-Year	3.7%

Sustainability forward default probability



Long-Term Rating Comparisons

Description		Value(pts.)	SCSS long-term
AAA	Prime	An obligor has EXTREMELY STRONG capacity to meet its sustainability commitments.	95 to 100
AA+	High grade	An obligor has VERY STRONG capacity to meet its sustainability commitments. It differs from the highest-rated obligors only to small degree.	90 to less than 95
AA			85 to less than 90
AA-			80 to less than 85
A+	Upper Medium grade	An obligor has STRONG capacity to meet its sustainability commitments but is somewhat more susceptible to the adverse effects of changes in circumstances than obligors in higher-rated categories.	75 to less than 80
A			70 to less than 75
A-			65 to less than 70
BBB+	Lower Medium grade	An obligor has ADEQUATE capacity to meet its sustainability commitments. However, adverse conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its sustainability commitments.	60 to less than 65
BBB			55 to less than 60
BBB-			50 to less than 55
BB+	Non-Investment Grade	An obligor is LESS VULNERABLE in the near term than other lower-rated obligors. However, it faces major ongoing uncertainties and exposure to adverse conditions, which could lead to the obligor "s inadequate capacity to meet its sustainability commitments.	45 to less than 50
BB			40 to less than 45
BB-			35 to less than 40
B+	Highly Speculative	An obligor is MORE VULNERABLE than the obligors rated "BB," but the obligor currently can meet its sustainability commitments. Adverse conditions will likely impair the obligor "s capacity or willingness to meet its sustainability commitments.	45 to less than 50
B			25 to less than 30
B-			20 to less than 25
CCC	Extremely Speculative	An obligor is CURRENTLY VULNERABLE and is dependent upon favorable conditions to meet its sustainability commitments.	15 to less than 20
CC		An obligor is CURRENTLY HIGHLY VULNERABLE.	10 to less than 15
C		An obligor is CURRENTLY HIGHLY VULNERABLE to sustainability breach	5 to less than 10
D	In default	An obligor has failed one or more of its sustainability obligations (rated or unrated) with negative results.	0 to less than 5
n.r.	Not rated	No rating has been requested, or there is insufficient information on which to base a rating.	Not applicable
r.w.	Rating withdrawn	The sustainability rating was withdrawn.	Not applicable